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The Feasibility of Co-location Detection through a Deep Learning Fusion of Mobile Sensors

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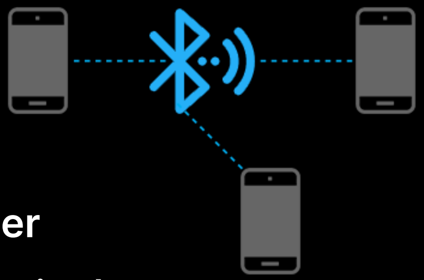
Challenges for Digital Proximity Detection in Pandemics: Privacy, Accuracy, and Impact

Outline

1. Background
2. Data
3. Network Architectures
4. Data Visualizations
5. Inconsistencies in the Data
6. Conclusion + Future Work

Background

- Detecting close contacts digitally, to effectively trace and isolate a possible spread
- Co-location detection methods have been proposed through various modalities, Bluetooth Low Energy (BLE) being the most widely accepted technology
- The received signal strength indicator (RSSI) value of BLE chirps is noisy (Leith et. al, 2020 - tinyurl.com/leith-ble)
- We proposed a joint deep learning model of BLE signals with other on-device sensors (Shankar et. al, 2020 - tinyurl.com/pcf-colocation)



Data

- Datasets collected by 2 separate organizations (NIST, MITRE) using the Structured Contact Tracing Protocol
- Further referred to as **TRAIN** and **TEST**

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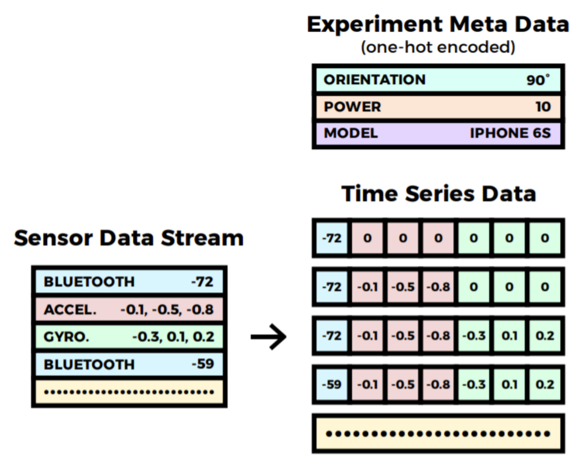
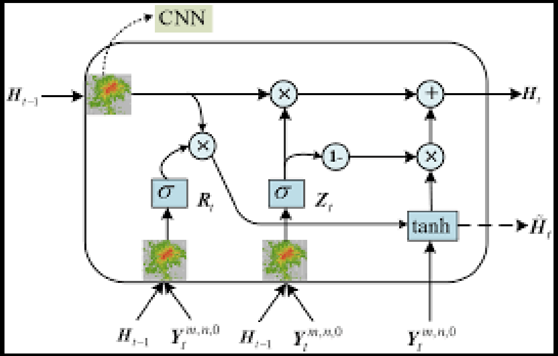


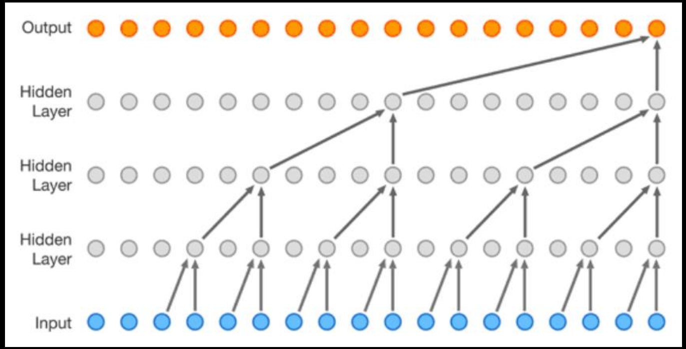
- Mobile sensor logs are converted into a numerical time series and concatenated with one-hot encoded experiment level metadata

Network Architectures

- Long short-term memory (LSTM) Network
- Gated Recurrent Unit (GRU)
- Convolutional Gated Recurrent Unit (ConvGRU)
- Temporal 1D Convolutional Network (Conv1D)



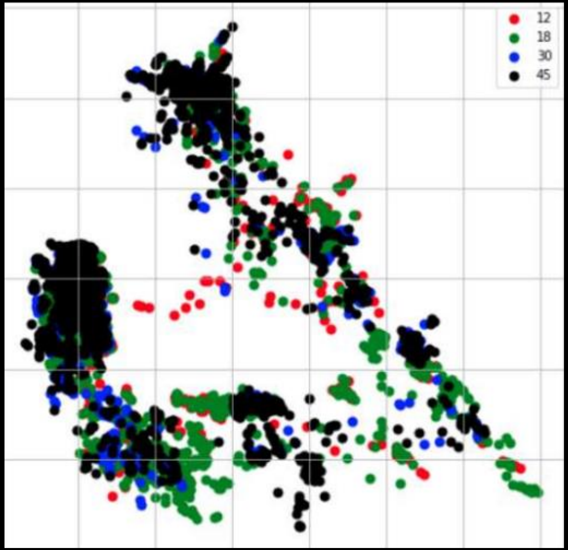
ConvGRU Network Architecture



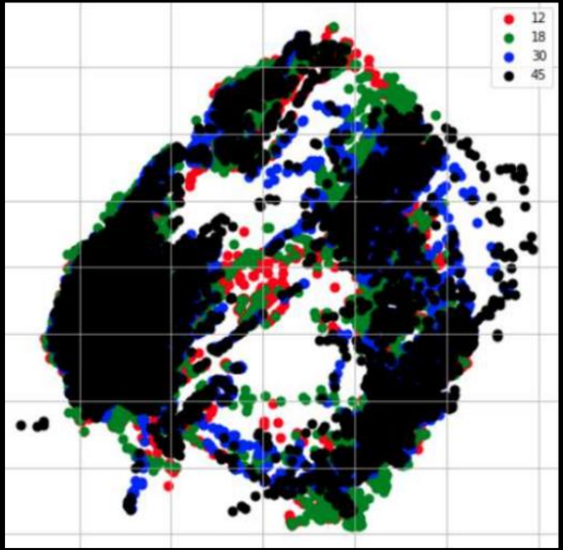
Conv1D Network Architecture

Inspired by DeepMind's WaveNet for Raw Audio

Data Visualizations



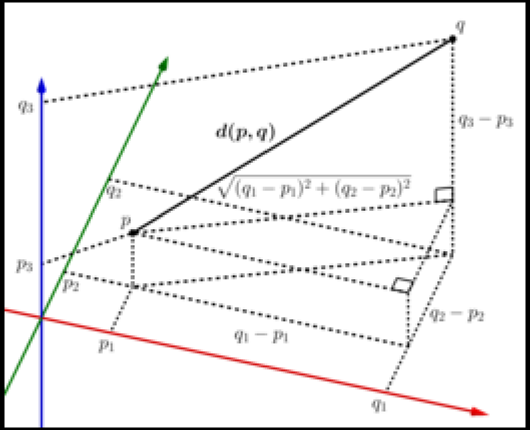
TRAIN



TEST

Inconsistencies in the Data

- Switching **TRAIN** and **TEST** datasets
- Training on an *optimal* NN subset of the TRAIN dataset
- Pairwise euclidean distance between feature vectors
  - Average l_2 between NN inter-bucket vectors: 200
  - Average l_2 between NN cross-bucket vectors: 24



Conclusion + Future Work

- Utilizing only BLE and mobile sensors data can detect proximity, but not at a high granularity (as needed for exposure risk applications)
  - Lack of generalizability within the data
- Dataset collection across different scenarios
- Extensive breakdown of mobile sensors contribution to prediction
- Physics-based forward model
- Integrating with other co-location technologies (Dmitrienko et. al, 2020 - tinyurl.com/pcf-wifi)

References

1. Sheshank Shankar, Rishank Kanaparti, Ayush Chopra, Rohan Sukumaran, Parth Patwa, Sunny Kang, Abhishek Singh, Kevin McPherson, Ramesh Raskar. Proximity Sensing: Modeling and Understanding Noisy RSSI-BLE Signals and Other Mobile Sensor Data for Digital Contact Tracing, 2020.
2. Douglas J. Leith and Stephen Farrell. Coronavirus contact tracing: Evaluating the potential of using bluetooth received signal strength for proximity detection, 2020.
3. Mikhail Dmitrienko, Abhishek Singh, Patrick Erichsen, and Ramesh Raskar. WiSense: WiFi Proximity Detection for Digital Contact Tracing, 2020.

PathCheck Foundation, an MIT spin-off

- World's largest open-source non-profit project for COVID-19
- Privacy first solutions for the pandemic and restarting economy
- Official contact tracing (G/A EN) mobile app for 5 US states, 3 countries
- Awards for Pandemic Response Work
  - Robert Wood Johnson Foundation Innovation Challenge
  - Facebook COVID-19 Symptom Data Challenge
  - NIST TC4TL Challenge
- Join the movement! Volunteers can join our slack: http://tiny.cc/pathcheckslack